Explanatory Pluralism: A Case Study from the Life Sciences

Version: June 1, 2021

Luis H. Favela[1, 2] and Anthony Chemero[3,4]

[1] Department of Philosophy, University of Central Florida

[2] Cognitive Sciences Program, University of Central Florida

[3] Department of Philosophy, University of Cincinnati

[4] Department of Psychology, University of Cincinnati

Author Note

Luis H. Favela https://orcid.org/0000-0002-6434-959X

Anthony Chemero https://orcid.org/0000-0001-5987-4106

Correspondence concerning this article should be addressed to Luis H. Favela, Department of Philosophy, University of Central Florida, 4111 Pictor Lane, Building 99, Suite 220, Orlando, FL 32816-1352. E-mail: luis.favela@ucf.edu

Abstract

The predominant view in the contemporary philosophies of the life sciences is that the most fundamental and viable kinds of explanations are mechanistic. In fact, some philosophers of the life science have claimed that the only genuine explanations in the life sciences are mechanistic. We believe this to be an unnecessarily restrictive position, both descriptively and normatively. Descriptively, much actual scientific research in the life sciences is not readily cast as mechanistic. There are many natural phenomena that benefit from the application of multiple explanatory strategies, even at the same scale of investigation. Thus, normatively speaking, research in the life sciences ought to begin from a pluralistic position concerning explanatory style. We defend this claim by means of the application of both mechanistic and dynamical explanatory strategies to bird flocking.

Keywords: bird flocking, dynamical explanation, explanatory pluralism, mechanistic explanation

Explanatory Pluralism: A Case Study from the Life Sciences

1. Introduction

For nearly 20 years, a number of philosophers have defended the claim that mechanistic explanations are the most fundamental kind of explanations in the life sciences. This claim is said to be both historically and normatively true (e.g., Bechtel & Abrahamsen, 2005, 2006; Craver, 2005, 2006, 2007; Craver & Bechtel, 2007; Craver & Darden, 2005, 2013; Darden & Craver, 2002; Machamer, Darden, & Craver 2000; Piccinini & Craver 2011). The reach of mechanistic explanations, it is claimed, not only applies to the biological sciences but also other special sciences such as economics (Craver & Alexandrova 2008; cf. Reiss, 2007). In keeping with this claim are arguments that alternative kinds of explanations, such as dynamical explanations, are worthwhile only insofar as they can augment mechanistic explanations (Bechtel & Abrahamsen, 2010, 2011; Kaplan & Bechtel, 2011; Kaplan & Craver, 2011). Many responses have been made in defense of dynamical explanations as being full explanations in themselves (e.g., Beer, 2000; Chemero, 2009; Favela, 2020a; Favela & Martin, 2017; Ross, 2015; van Gelder, 1998; Yoshimi, 2012). However, we think there is an issue in the debate that has not received enough attention, namely, the restrictive nature of adhering to "one size fits all" explanatory frameworks. In short, we think adhering to the mechanism-only position results in unnecessarily limited conceptions of the world. Whether implicitly or explicitly, to adhere to a position that mechanistic explanations are fundamental is to simultaneously adhere to the idea that science investigates a world populated mechanisms (Mitchell, 2002; Wright & Bechtel, 2006, pp. 59-61). The same goes for dynamical-only explanations. We believe this to be an unnecessarily restrictive position, both descriptively and normatively. Descriptively, much actual

scientific research in the life sciences is not readily cast as mechanistic (e.g., see Chialvo's discussion of non-mechanistic approaches topics such as biological organisms, glassy states, language, proteins, and turbulence; 2018). There are many natural phenomena that benefit from the application of multiple explanatory strategies, even at the same scale of investigation. Thus, normatively speaking, research in the life sciences ought to begin from a pluralistic position concerning explanatory style (e.g., Suppes, 1978).

The world is tremendously complex. Moreover, there are various explanatory goals that guide and motivate investigations. In light of these facts, we believe that investigations in the life and other special sciences ought to begin from an agnostic position concerning the nature of the phenomena under inquiry (Chemero & Silberstein, 2008; Dale, 2008; Dale, Dietrich, & Chemero, 2009; Godfrey-Smith, 2010; Love, 2012; Sterelny, 1996). To start from an agnostic position is to be open to pluralism. If we are to be pluralistic, then we should not exclude *a priori* the prospect of multiple empirically reasonable theoretical frameworks. Of course, all investigations must start somewhere. However, investigations need not all start from the same place, nor do all investigations need to start with the same theoretical commitments. Moreover, in some cases there is no single kind of explanation that will account for all aspects of a single phenomenon. In other words, there are cases in which no single path to discovery will be able to account for the *True* total nature of a phenomenon. Along these lines, the central argument we defend here is as follows:

P1. Mechanistic explanations appropriately account for some natural phenomena.

P2. Mechanistic explanations are not always reducible to other kinds of explanations.

P3. Dynamical explanations appropriately account for some natural phenomena.

P4. Dynamical explanations are not always reducible to other kinds of explanations.

P5. There are natural phenomena with different features amenable to varying explanatory strategies.

P6. The explanatory strategy appropriate for those different features are not reducible to other explanatory strategies.

C1. There are natural phenomena that require multiple explanatory strategies.

C2. There are natural phenomena that require both mechanistic and dynamical explanations.

Conclusions one and two underlie the necessity for explanatory pluralism in the life sciences. We demonstrate this and explanatory pluralism by means of a case study. The case study is that of bird flocking, specifically, starling murmurations. We proceed by first giving an account of mechanistic and dynamical explanations. Then, we present our case study: bird flocking. After, we describe mechanistic and dynamical explanations of different aspects of bird flocking at the same scale of investigation. We then address the challenge from proponents of dynamic mechanistic explanations. Finally, we elucidate why this case supports the notion of explanatory pluralism. In particular, we make clear how a devotion to explanatory monism prevents one from being able to account for certain features of a natural, biological phenomenon. Being an explanatory pluralist allows one to account for those features.

2. Mechanistic and Dynamical Explanations

What follows are accounts of mechanistic and dynamical explanations. Given the enormous size of the relevant literature, we *do not* claim to provide all encompassing accounts of mechanistic or dynamical explanations. Instead, we intend to highlight *some* of the typical characteristics of those explanations, particularly those that we understand as being difficult to

reconcile and which we take as underlying reasons why the two approaches are often viewed as at odds with each other. Moreover, we focus on those aspects of these two explanatory strategies that are explicitly utilized in scientific practice.

2.1 Mechanistic explanations

There are numerous versions of "mechanistic explanations" (for a very small sample see Bechtel, 2008; Bechtel & Richardson, 1993/2010; Craver, 2007; Glennan, 2005; Machamer, Darden, & Craver, 2000; etc.). Though there are a number of sophisticated philosophical accounts of mechanistic explanation in recent years (for review see Glennan & Illari, 2018), here we limit ourselves to early work that can broadly be conceived as the "new mechanism" that appeared in the 1990s and early 2000s (i.e., Bechtel & Richardson, 1993/2010; Machamer et al., 2000). We limit our discussion to that conception of mechanistic explanation for two reasons. First, attempting to synthesize the literature into a single "mechanistic framework," while properly treating the relevant work, is far beyond the scope of the current work. Second, we take the early work by people such as Bechtel and Richardson to be attempts at understanding heuristics utilized by scientists in their research (1993/2010, e.g., pp. xiii-xiv, xix, 37, 236); heuristics that we take to still be central to practice in the life sciences. Accordingly, we utilize "mechanistic explanation" as referring to three main features: linearity, localization, and component dominance. Before explaining each of those features, we begin with a general description of a mechanistic explanatory strategy. In very broad terms, a mechanistic explanation is one in which the behavior of a system is accounted for in terms of the functions and interactions of its parts (Bechtel & Richardson, 1993/2010, p. 17). "Mechanisms" are the entities and activities whose organization exhibits the explained phenomenon (Craver, 2007). The

organization of these entities and activities produce regular changes from start or set-up to finish or termination conditions (Craver & Darden, 2013, p. 15; Machamer et al., 2000).

The methods utilized to bring about these explanations are those of decomposition and localization. As Bechtel and Richardson describe it, decomposition allows for "the activity of a whole system [to be treated] as the product of a set of subordinate functions (1993/2010, p. 23). Moreover, these interactions are accounted for in a manner that is additive and linear (1993/2010, p. 23). Localization is the investigative process by which "the different activities proposed in a task decomposition [are identified] with the behavior or capacities of specific components" (1993/2010, p. 26). A mechanistic explanation is achieved when a phenomenon's mechanisms are described (Machamer et al., 2000). With this general picture of mechanistic frameworks and explanations in mind, we now focus on three of the main commitments of mechanistic explanations: linearity, localization, and component dominance.

The first commitment underlying mechanistic frameworks is linearity. Machamer, Darden, and Craver state that, "Mechanisms are entities and activities such that they are productive of regular change from start or setup to finish or termination conditions" (2000, p. 3). Such a conception of mechanisms should not be surprising since one of the heuristic assumptions of human bounded rationality is that humans often think of events as occurring linearly (Bechtel & Richardson, 1993/2010, p. 18). In other words, humans think about events in sequential and step-by-step terms: "Why did D happen? Because first A, then B and C, and then D." In order to reveal the significance such commitments to linearity have, it is informative to look at how linearity constrains the way data is analyzed.

Linearity can be understood as a temporal factor in that phenomena are the result of sequential steps. As long as the steps in a particular linear process are followed, then particular

outcomes are guaranteed. When conceived of as a temporal factor, linearity can be understood structurally, where "structure" refers to the relations of parts. In that way linearity can be understood as a kind of additivity (Sternberg, 1969), and can be summed up in the following equation (Eq. 1; Ivancevic & Ivancevic, 2007, p. 52):

$$f(x + y) = f(x) + f(y) \quad (1)$$

The idea that the equation captures is that a phenomenon, *f*, can be characterized as composed of components *x* and *y*, or *f* can be characterized as components *x* and *y* added together. The phenomenon *f* is nothing more or less if it is conceptualized as being a unit comprised of parts *x* and *y* or as a phenomenon comprised of part *x* added to part *y*.

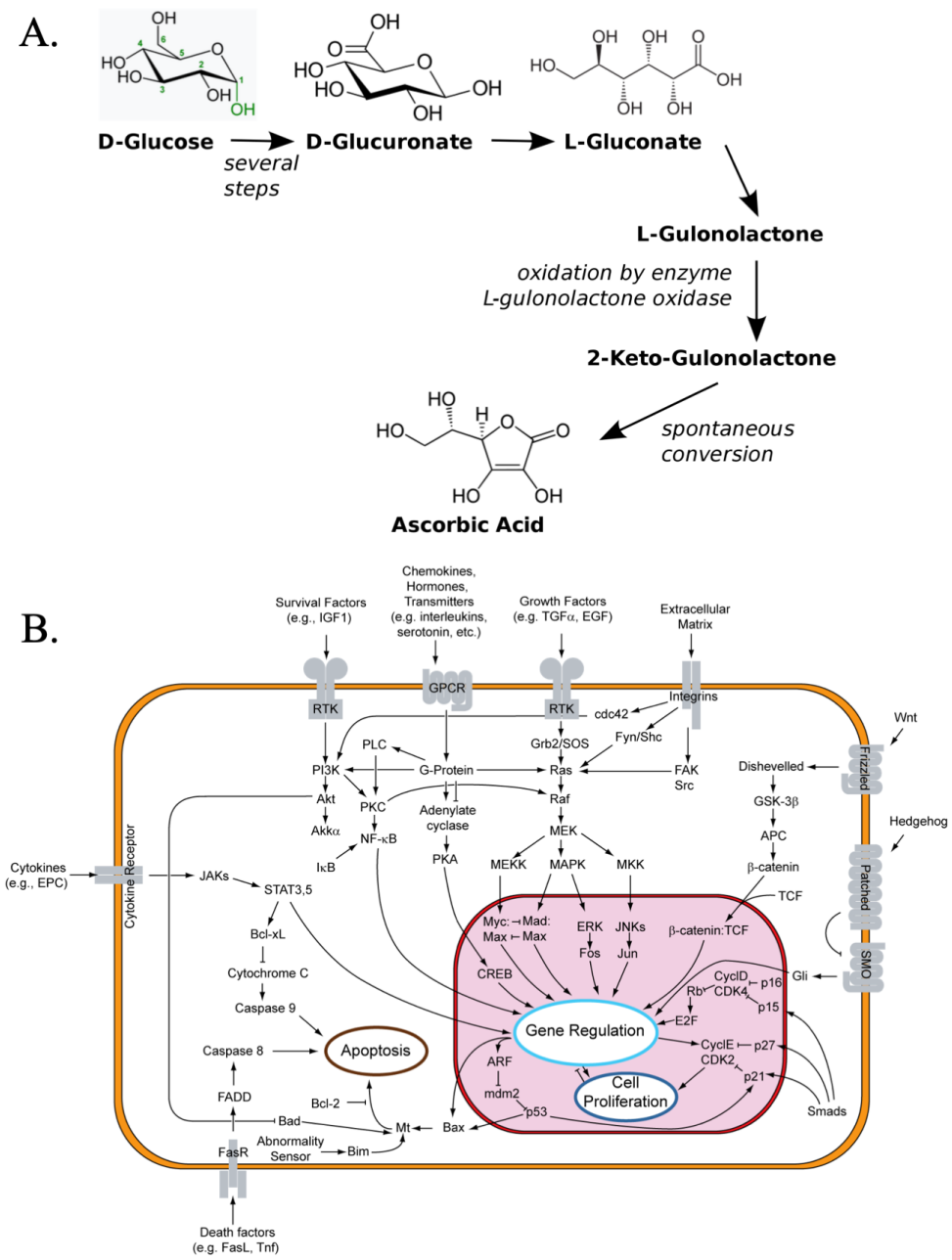
If a phenomenon is linear, and if it is additive, then it should follow that the effects of perturbations on the system are localized in individual components (Holden, Van Orden, & Turvey, 2009, p. 319). Systems that are the result of additive dynamics can be described as having *weak interactions* (Holden et al., 2009). They are "weak" because system-level behaviors are primarily the result of their parts added together. Consider a system *S* comprised of parts *X*, *Y*, and *Z*. If the properties of *S* are the result of additive relations among *X*, *Y*, *Z*, and if $X = 1$, $Y = 2$, and $Z = 3$, then *S* will have property *6* ($S_{X,Y,Z}$), specifically, the result of an additive relationship among *X*, *Y*, and *Z* ($1 + 2 + 3 = 6$). Thus, if *X* were perturbed such that property 1 was "knocked out" (e.g., when a neuron receives a "block" and is cutoff from inputs from other neurons), then *S* should have a resulting property 5 ($S_{y,z}$). System *S* goes from property 6 to property 5 because perturbing *X* alone does not affect the properties of *Y* or *Z*. Such a system can be understood as being component dominant.

Component dominance refers to cases where a system's behaviors result from additively and linearly organized parts with rigid architecture and predetermined functions. A component-

dominant system is one that can be decomposed into distinct functional units of a larger system (Richardson & Chemero, 2014). Where the relevant components "bottom out" is a matter of debate (e.g., Kuhlmann & Glennan, 2014). Though for current purposes, we can understand the "lowest level" components as those that are experimentally revealed to be the spatial (e.g., size), temporal (e.g., duration), and causal (e.g., feedback) parts of the mechanism under investigation (Povich & Craver, 2018, p. 106). One way to identify components is to first assume the phenomenon under investigation is additive. In order to reveal additivity, the phenomenon is decomposed in order to localize specific capacities. When the data from the parts are analyzed, they should demonstrate component-dominant dynamics, that is, weakly interacting parts, with local affects that can be summed to reveal the whole behavior. If the parts of the system can be summed to reveal the whole behavior, then the commitments to linearity, additivity, localization, and component dominance was the correct one. Both artifacts and natural phenomena can exhibit additivity, linearity, and component dominance. Artifacts include combustion engines, pocket calculators, and toilets. Natural phenomena include Shepherds' account of chemical transmission at synapses (Machamer et al., 2000, pp. 8-13), long-term potentiation (Craver, 2005), vitamin C biosynthesis (Figure 1A), and major signal transduction pathways (Figure 1B). Again, as we stated at the start of this section, our aim was not to synthesize the large and sophisticated philosophical literature on mechanisms. Instead, we merely aimed to present a form of mechanistic explanation that we take to be common in scientific practice. In the following section, we take the same approach with dynamical explanations.

Figure 1

Common Biological Mechanisms



Note. Schematics of biological mechanisms can be as relatively straightforward as the mechanism for vitamin C biosynthesis in vertebrates (A); or as complicated as major signal transduction pathways in mammals (B). (Copyright Wikipedia CC BY-SA 3.0 and CC BY-SA 4.0.)

2.2 Dynamical explanations

The philosophical literature on dynamical explanations is not nearly as vast or controversial as that for mechanisms; this is especially true for special sciences (for discussion, see Favela, 2020b). This may be due to philosophers inheriting a clearer articulation of the concepts and methods from engineers and scientists who broadly agree on their definition and usage (for review see Strogatz, 2018). Dynamical explanatory strategies typically center on accounting for the relevant variables within a set of differential equations and depicting the phenomenon in a phase space, which, following the variables in the equations, represents all possible states of the system and how the system evolves over time. Although there are linear dynamical systems, much of the appeal and power of dynamical systems theory stems from its ability to capture nonlinear phenomena. Dynamical explanations tend to focus on the principles responsible for a system's spatial and temporal structure. Such explanations are similar, though not equivalent, to covering law explanations, are counter-factual supporting, and provide evidence for unification of apparently distinct phenomena (Stepp, Chemero, & Turvey, 2011, pp. 432-435).

When thinking about the nature of dynamical explanations, the first thing to keep in mind is that dynamical explanations seek to accomplish something very different than mechanistic explanations. As discussed in the previous section, mechanistic explanations tend to focus on identifying the constitutive components and properties of the components of the phenomenon. Dynamicists tend to be interested in discovering principles, how widely they apply in nature, and how they can be predicted and manipulated in order to facilitate understanding of complex phenomena. Instead of the constituents of a phenomenon, dynamical explanations are about

discovering how the states of a system evolve over time according to a principle (Riley & Holden, 2012). These principles are often written captured via differential equations, which are suited due to their ability to express temporal features of a system. Nonetheless, for an investigator to *understand* how the system evolves, having access to a model and solving the equations is not always enough. That is why it is typical for an investigator to plot the equation in a state space, which contains all possible states of the system over time (Kelso, 1997). Having a qualitative interpretation of a system (i.e., a state space, phase space portrait, etc.) facilitates understanding for an investigator in a way that equations alone do not.

As mentioned above, the dynamical systems treatment of a phenomenon includes capturing the phenomenon in a phase space that represents all possible states of the system and how the system evolves over time. Such pictorial depictions of a system can facilitate understanding a system in a way that abstract equations might not. Take the example of the bursting behavior of a single neuron (Izhikevich, 2007). Izhikevich's "simple" model of spiking neurons is represented via the following two coupled differential equations (Izhikevich, 2010, p. 5063, equations 2.1 and 2.2):

$$C\dot{v} = k(v - v_{\text{rest}})(v - v_{\text{thresh}}) - u + I \tag{2.1}$$

and

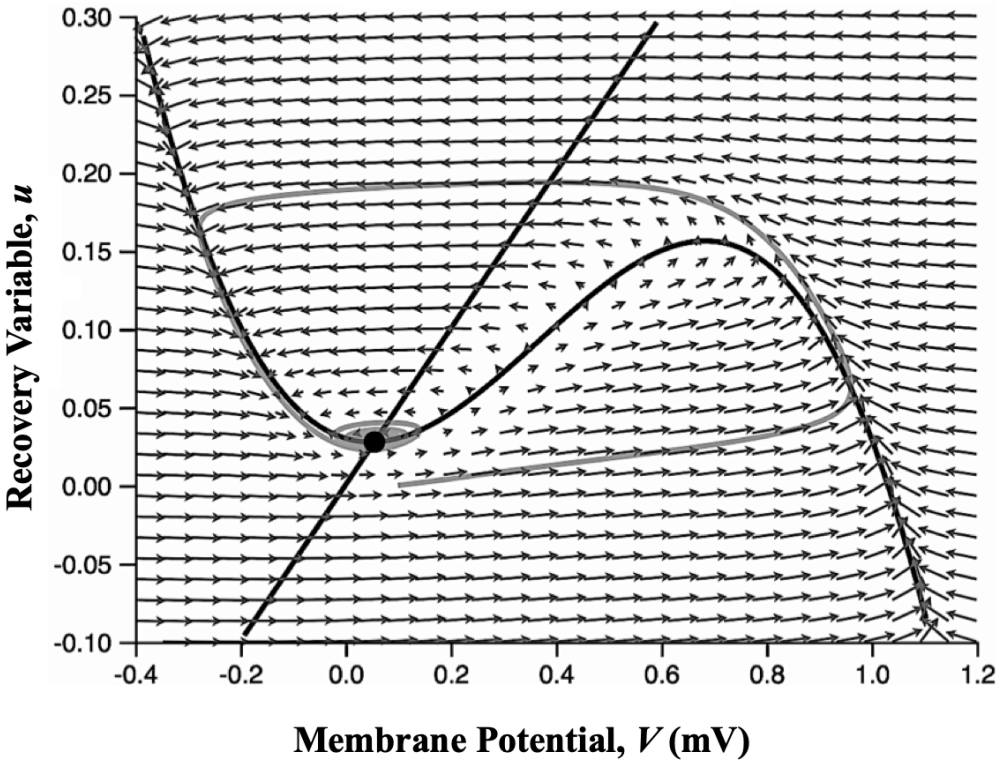
$$\dot{u} = a[b(v - v_{\text{rest}}) - u] \tag{2.2}$$

With these two equations, the entire range of firing behavior of a pyramidal neuron is captured. The equation in the first part of the model (2.1) captures factors responsible for a single neuron's membrane potential (v), or firing. The second equation (2.2) captures factors responsible for the recovery, or repolarization, of a single neuron (u).

Although this simple model is biologically realistic, Izhikevich points out that solving (i.e., understanding) the model of the firing behavior of the neuron is difficult to achieve analytically (2007, pp. 43, 81, 270). In this situation, "analytic" means obtaining knowledge about the behavior of the system by actually solving the equations. Solving differential equations is fundamental to the utilization of such methods. In order to solve a differential equation, one must find a function that specifies a rule that determines values of the dependent variable and does not change the dependent variables (Brown, 2007, p. 13). Thus, in order to solve or understand the model, it is necessary to plot it in a phase space (Figure 2). This phase space portrait allows the qualitative behavior of a complex system (single neurons) to be analyzed via a model with two differential equations (2.1 and 2.2), all in terms of a simple two-dimensional plane that shows the entire range of behaviors of the system over time. Understanding is facilitated by limiting the causally relevant factors to two dimensions: recovery variable *u* and membrane potential *v*. This strategy is particularly well-suited for investigating phenomena with two particular characteristics: nonlinearity and interaction dominance.

Figure 2

Phase Space Portrait of Izhikevich Model of Spiking Neurons



Note. Phase space portrait of Izhikevich model of spiking neurons (2010, p. 5063; equations 2.1 and 2.2). As part of the dynamical explanatory strategy, plotting equations on a two-dimensional plane can provide a qualitative understanding of a model otherwise too complicated to solve analytically. (Modified with permission from J. Terwilliger, 2018. Retrieved October 24, 2018 from http://jackterwilliger.com/biological-neural-networks-part-i-spiking-neurons/)

Nonlinearity refers to the dynamics of systems whereby the output is not directly proportional to the input (Carello & Moreno, 2005). This is in contrast to linear systems that are additive in that outputs are directly proportional to inputs. As discussed in the previous section, if a phenomenon is linear, and if it is additive, then it should follow that the effects of perturbations

on the system will reveal “weak interactions” localized in individual components (Holden, Van Orden, & Turvey, 2009, p. 319). Systems that are nonlinear, on the other hand, are not typically comprised of weakly interacting components. Thus, instead of being component dominant, nonlinear systems can be interaction dominant.

Interaction dominance refers to a kind of dynamics exhibited by a system. Systems are interaction dominant when the dynamics or properties of the interactions among the parts supersede those that the parts would have separately or if the parts contributed to a system via additive interactions (Holden et al., 2009; Silberstein & Chemero, 2013; Silberstein, 2021). Interaction-dominant systems can also be described as non-modular or non-decomposable. When a system is modular, decomposable, and component dominant, then the properties of the system result from the properties of the component parts “added” together. In this way, the composition and capacities of parts can be the primary cause of the dynamics of the system. Mechanistic explanation is appropriate in these cases because when a system is component dominant, then the strategy of decomposition and localization works quite well. However, in the case of systems with interaction-dominant dynamics, the method of decomposition and localization is not usually effective, as the properties of interaction-dominant systems result primarily from the dynamic interactions of the components. It is possible to figure out how the properties of the components contribute to the dynamics of the system, but only when examined post-hoc. In other words, if an investigator were presented with a set of components, and if she were not permitted to observe how those components act as a system, then it is unlikely—if not impossible—to predict what the system’s behavior would be. In some cases, this is due to the fact that components of interaction-dominant systems can have properties that result from non-additive interactions (Carello & Moreno, 2005; Sternberg, 1969, 2011).

In the previous section, we described a linear and additive system, *S*. Let us look at a nonlinear and non-additive system, *S**. If *S** is comprised of *A*, *B*, *C*, where *A* =1, *B* = 2, and *C* = 3, but the interactions among *A*, *B*, *C* are nonlinear, then swapping out *A* for *D* (*D* = 4) could alter the interactions of the entire system. So, if *S** is a nonlinear and non-additive system, then the system-level activity could be exponential or multiplicative, for example: *S** = 24 (where $S^*_{D,B,C}$ [4 × 2 × 3 = 24]) or *S** = 96 (where $S^*_{D,B,C}$ [4^2 × 2 × 3 = 96]). In this way, we can also see what happens to a system that is interaction dominant.

Interaction-dominant systems have system-level properties that override the properties of the components. In a component-dominant system, where the interactions of the components are additive, the properties of the whole system are no more or less than the properties of the components: System $S_{X,Y,Z}$ (*X* =1, *Y* = 2, and *Z* = 3) has property 6 if the interactions are additive (1 + 2 + 3 = 6). In an interaction-dominant system where the interactions are nonlinear (i.e., exponential or multiplicative), the interactions of the components are altered based on the nature of the system as a whole: System $S^*_{D,B,C}$ (*D* = 4, *B* = 2, and *C* = 3) has property 39 if the interactions are additive ($[4 + 2]^2 + 3 = 39$) or property 192 if the interactions are multiplicative ($[4 \times 2]^2 \times 3 = 192$). In the previous two examples, the brackets and exponent are intended to capture the nonlinear effects upon an interaction-dominant system, that is, how the place within a system can alter the properties within that system.

This concludes our descriptions of mechanistic and dynamical explanations. As we mentioned at the start of this section, given the enormous size of the relevant literature, we have not intended to provide comprehensive accounts of mechanistic or dynamical explanations. Instead, we focused on the characteristics that most clearly differentiate them, specifically, the emphasis on linearity and component dominance typical to mechanistic explanations, and the

emphasis on nonlinearity and interaction dominance of dynamical explanations. Moreover, we focused on conceptual and methodological commitments that we take scientific practitioners to adhere to when their work expresses commitments to mechanistic or dynamical features. With these accounts given, we can proceed to our case study in explanatory pluralism.

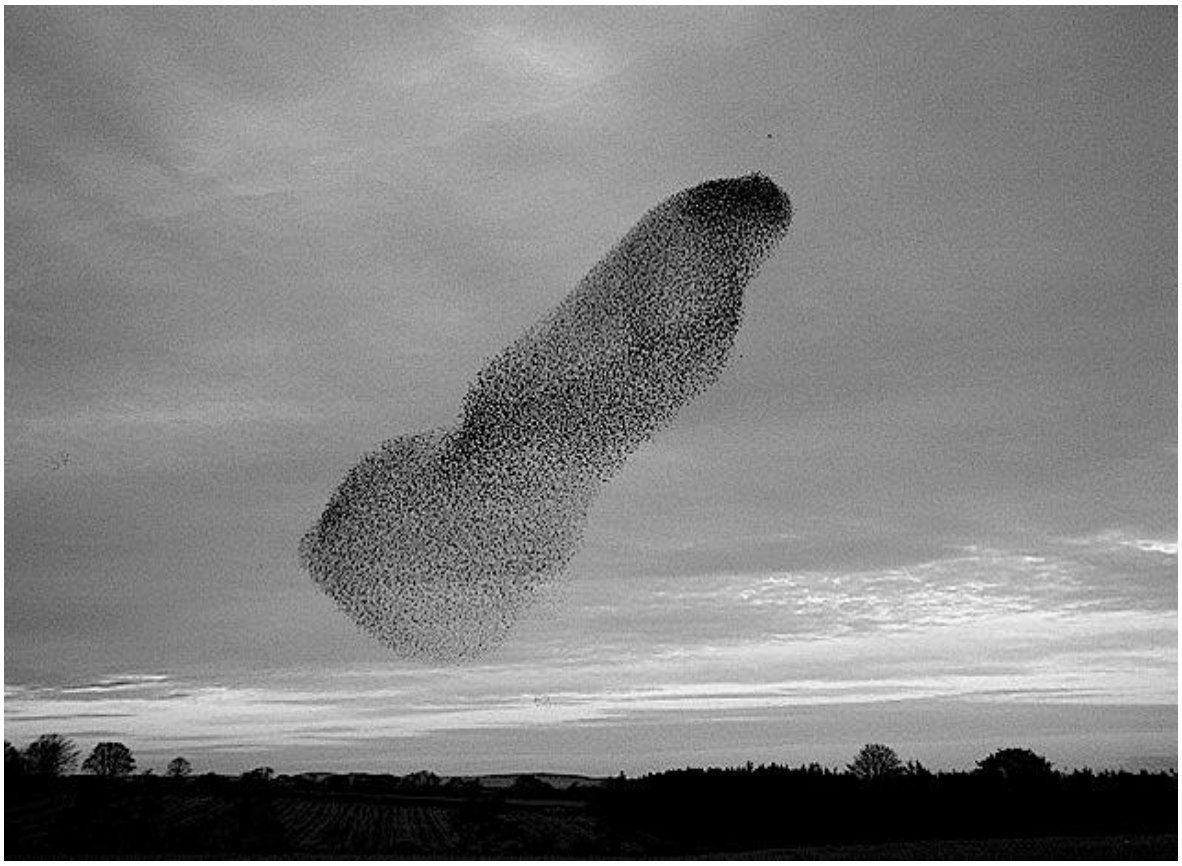
3. A Case Study

Starlings (*sturnus vulgaris*) are a family of small to medium-sized birds found in many places around the world including Asia, Europe, and North America. Among other things, starlings are known for their murmurations. A "murmuration" is a flock of starlings. Starling flocks can number in the hundreds to thousands. What makes these flocks noteworthy is their globally unified behavior. Murmurations are a coordination phenomenon in which interactions between individuals produce collective, large-scale patterns (Bialek et al. 2012, p. 4787). To watch a flock of starlings during the day is to see a single, dark, and large blob-like form moving about and taking on various shapes in the sky (Figure 3). No matter the directions or shapes, the flock maintains movements that appear collective, synchronous, and ordered in a global manner (Cavagna et al. 2010, p. 11865). Explaining such collective animal behavior is very difficult, particularly if you want to explain how each bird has the nearest neighbors that it has at a particular time. This problem is further confounded if you want your explanation to be done with a few simple rules and variables. There are two explanations that have come to the forefront in the literature on bird flocking (Bialek et al. 2012; Cavagna et al. 2010; Cavagna et al. 2013a; Cavagna et al. 2013b; Kattas et al. 2012; Procaccini et al. 2011). One explanation is mechanistic and accounts for scale-free behavior and bird orientation. The other explanation is dynamical and accounts for scale-free behavior and bird velocity. Each will be presented in turn. It is crucial to

keep in mind that both are applied at the same level of analysis, that is, the biobehavioral scale at which flocking occurs.

Figure 3

Starling Flock



Note. Starling flock in Gretna, Dumfries and Galloway, Scotland. (Source: Walter Baxter. Creative Commons Attribution-Share Alike 2.0 Generic License. Retrieved September 25, 2013 from http://www.geograph.org.uk/photo/1069366).

3.1 Mechanistic explanation of orientation in bird flocking

When attempting to account for bird flocking behavior, the mechanistic explanation

attempts to answer the following question: How does the behavior of bird *X* navigating amongst its nearest neighbors, Y_1-Y_7, result in scale-free correlations? "Scale-free" refers to the behavior of the flock as a whole such that the "behavioral change of one individual influences and is influenced by the behavioral changes of all other individuals in the group" (Cavagna et al. 2010, p. 11866). One aspect of this question involves providing an explanation for the *orientation* of each bird. The mechanistic explanation for this feature of the phenomenon posits the maximum entropy model (Bialek et al. 2012). This model accounts for the location of nearest neighbors by starting from the individual bird and explaining outwards towards the flock. The model also attempts to account for the effect of one bird's movements as cascading throughout the flock. As a result, the flock is understood primarily as a group of individual birds.

In utilizing the maximum entropy model, the mechanist need only posit "[s]imple behavioral rules based on imitation" to account for coordination among nearest neighbors (Cavagna et al. 2010, p. 11869). The behavior based on imitation that the maximum entropy model ascribes to individual members of flocks are treated as tantamount to the behavior of ferromagnetism. Ferromagnetism is the kind of magnetic force that most people are familiar with. Demonstrations of ferromagnetism include, for example, the forces responsible for magnets sticking to refrigerator doors and two magnets repelling from one another when both of their positive charged sides are facing each other (Newman, 2008; Sandeman et al. 2008). Similarly, individual birds are treated as individual magnets: birds have a front and back end, and magnets have a positive and negative end.

If individual birds are accurately treated as individual magnets, then a model of the individual birds based on such magnetic properties should be consistent with actual flock movements (i.e., maximum entropy distribution; Bialek et al. 2012, p. 4786). Bialek et al. (2012)

provide the following model (Eq. 4),

$$P(\{\vec{S_i}\} = \frac{1}{Z(J, n_c)} \exp \left[[\frac{J}{2} \sum_{i=1}^{N} \sum_{j \in n_c^i} \vec{s_i} \cdot \vec{s_j}] \right] \quad (4)$$

where $j \in n_c^i$ refers to individual bird j belonging to group n_c with nearest neighbors i. As Bialek et al. (2012) demonstrate, the model provides simulations that are indeed consistent with experimental correlations in large flocks of starlings. From this core model, further models following the same rules of ferromagnetism, which underlie maximum entropy distribution, can provide other specific information, such as the orientation of multiple birds (Eq. 5),

$$C_{\text{int}} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{n_c} \sum_{j \in n_i^c} \langle \vec{S_i} \cdot \vec{S_j} \rangle \approx \frac{1}{N} \sum_{i=1}^{N} \frac{1}{n_c} \sum_{j \in n_c^i} \langle \vec{S_i} \cdot \vec{S_j} \rangle. \quad (5)$$

where n_c refers to orientations of neighborhood of birds. A powerful feature of the basic model in Eq. 4 is that in addition to providing the orientation of individual birds in a flock, it also exhibits the scale-free structure of the flock as a whole. Thus, modifications to the model, such as Eq. 5, allow for the comparison of flocks of various sizes without compromising the experimentally consistent scale-free behavior among flock orientations (Bialek et al. 2012). Whether tracking individual birds (e.g., j in Eq. 4) or two or more birds (e.g., n_c in Eq. 5), it is the influence of the individual upon the group that is captured via the models. Since the models are consistent with experimental data (i.e., movements of real bird flocks), it is reasonable to understand that individual bird orientation is driven via a local (i.e., individual bird) process. Moreover, such local processes also contribute to the scale-free structure of the flock as a whole.

By modeling the flocks as being composed of birds with magnet-like rules of behavior, the maximum entropy model accounts for the location of each nearest neighbor, with the added benefit of also capturing the flock's apparent scale-free coordination. The explanation is

mechanistic because the basic tenets of a mechanistic explanation remain, namely, that of linear decomposition and localization: the coordination behavior of the whole flock can be treated as the product of decomposable linear activities that are localizable in the individual birds. Once decomposed and localized, the coordination of the individual birds in the flock can be modeled in a manner similar to the ferromagnetic forces.

3.2 Dynamical explanation of velocity in bird flocking

As with the mechanistic explanation, when attempting to account for bird flocking behavior, the dynamical explanation attempts to answer the following question: How does the behavior of bird *X* navigating amongst its nearest neighbors, Y_1-Y_7, result in scale-free correlations? As stated above, "scale-free" refers to the behavioral change of individuals influencing the flock as a whole. One aspect of this question involves providing an explanation for the *velocity* of each bird. The dynamical explanation for this feature of the phenomenon posits the superdiffusion model (Cavagna et al. 2013a). This model accounts for the velocity of each bird by starting from the flock as a whole and explaining inwards towards the individual. In other words, this approach treats the flock as the primary system to be explained, whereas the mechanistic model above treated the individual birds as requiring the primary explanation. The superdiffusion model also accounts for the effect of the velocity of the flock as a whole cascading throughout to affect the velocity of each individual bird.

The dynamical explanation accounts for the velocity of a bird and its nearest neighbors in terms of their behavior resulting from diffusion taking its course: at each instant of time each bird is interacting with whatever birds have been brought there by their superdiffusive wandering throughout the flock (Cavagna et al. 2013a, p. 5). In physics, diffusion is the process by which

particles seem to spread randomly, often to the point of equilibrium if environmental conditions suffice (Newman, 2008, pp. 15-16, 33-36). When superdiffusion occurs in scale-free systems, particles (or birds) will explore space via nonlinear processes (ben-Avraham & Havlin, 2004, pp. 57-72; Li et al. 2011).

If bird flocks do indeed move via superdiffusion, then the model should demonstrate individual bird movements that are consistent with actual flock movements. Cavagna et al. (2013) provide the following model (Eq. 6) to capture the diffusion processes of the flock,

$$\delta R^2(t) = Dt^a \tag{6}$$

where δ is the change of the position of birds R at time t, a is the diffusion exponent, and D is the diffusion coefficient. Simulations of the model are consistent with experimental observations of bird flocks. The following model (Eq. 7) is derived from Eq. 6 in order to calculate bird velocities,

$$\delta r^2(t) \equiv \frac{1}{T-t}\frac{1}{N}\sum_{t_0=0}^{T-t-1}\sum_{i=1}^{N}[\boldsymbol{r}_i(t_0+t) - \boldsymbol{r}_i(t_0)]^2 \tag{7}$$

where $\boldsymbol{R}_{CM}(t)$ refers to the position of the center of the flock at time t and $r_i(t) = R_i(t) - R_{CM}(t)$ refers to the position of a bird i in the flock. Along with the number of birds in the flock N and the time series length T, the velocity of the flock can be calculated. A powerful feature of Eq. 4 is that in addition to providing the velocity of the flock, it also maintains the scale-free structure of the flock as whole. This is accounted for by treating the individual birds as relating to the whole flock as if they are individual particles within a body of fluid. Moreover, the relationship of bird to flock and vice versa—as particle to fluid and vice versa—is nonlinear. Specifically, the velocity affects the flock via cascades that are not additive (i.e., linear), but multiplicative (i.e., nonlinear). Such a nonlinear relationship contributes to explanations of

velocity resisting the methods of decomposition and localization, namely, methods more appropriate to phenomena comprised of additively/linearly related components. By modeling the flock as a single superdiffusive system, the superdiffusion model accounts not only for the velocity of each bird, but also for the scale-free coordination of the flock. Moreover, accurate predictions can be made of the velocities of the birds within the flock, thereby negating the need to decompose the flock and localize individual birds (Cavagna et al. 2013a, pp. 7-8).

4. Dynamic Mechanistic Explanations

As stated in the introduction, the predominant view in the philosophies of the life sciences is that it is both historically and normatively true that mechanistic explanations are the most fundamental kind of explanations in the life sciences. There is a lot to be said for that position, not least of which is the descriptive fact that the term ‘mechanism’ is commonly used in the life sciences. There are countless examples of this in neuroscience alone, where questions are typically stated in the form of, “What are the mechanisms of: Alzheimer’s, memory, pleasure and displeasure, stress, theta rhythms, vision, etc.?” With that said, proponents of mechanistic explanations in the life sciences have been challenged by phenomena that resist typical mechanistic methodologies (i.e., decomposition and localization) and conceptualizations (e.g., linearity and component dominance). The challenges come from phenomena that are nonlinear and interaction dominant in nature. So, what happens when a proponent of mechanism-only explanations is faced with a phenomenon that lends itself to nonlinear dynamical, graph-theoretic, or topological concepts and methods? Such folks tend to break into two camps: One camp argues that those concepts and methods are not parts of explanations insofar as they are not mechanistic explanations (e.g., Craver, 2007; Darden & Craver, 2002; Kaplan & Bechtel, 2011;

Piccinini & Craver, 2011). The other camp says that those concepts and methods are parts of explanations insofar as they are part of *dynamic mechanistic explanations* (DME; e.g., Bechtel & Abrahamsen, 2010, 2011, 2013; Kaplan, 2018; Levy & Bechtel, 2013).

Proponents of DME typically make two moves: import methods from other explanatory frameworks and/or redefine 'mechanism' to include concepts from other explanatory frameworks. Bechtel and Abrahamsen (2013) provide an illustrative example of the "import methods" move. Bechtel and Abrahamsen argue that a DME account of circadian rhythms involves decomposing the phenomenon into component parts and operations, then recomposing the components via computational models that include differential equations corresponding to the parts and operations (2013, pp. 707-708). We do not think this approach is actually anything more than a mechanistic explanation, albeit one that uses calculus to bolster the conceptual and methodological commitments. Merely corresponding differential equations to components does not make an explanation "dynamical," that is, in the sense we described "dynamical explanations" above. Thus, utilizing calculus cannot be a differentiating factor among dynamical, mechanistic, and DME. Besides, plenty of classical computational explanations and the like use calculus (e.g., Eliasmith & Anderson, 2003; Harnad, 1993; Pylyshyn, 1984; see discussion by Lamb & Chemero, 2018). Mechanistic explanations adhere to the method of decomposition and localization; Bechtel and Abrahamsen's DME does that. Mechanistic explanations are also component dominant; Bechtel and Abrahamsen's DME is also, albeit with the addition of differential equations to correspond with the components. What makes "dynamical explanations" interesting is not their use of differential equations. Dynamical explanations are interesting only insofar as the phenomena they investigate exhibit properties different than or incommensurable with those of other explanatory strategies, such as interaction dominance.

The second move made by DME proponents when faced with a phenomenon that resists mechanistic methods and/or concepts is to redefine what a "mechanism" is. Proponents of DME do not abandon mechanistic frameworks when a phenomenon is, for example, interaction dominant. Instead, they expand the purview of mechanistic explanations to include phenomena they had not before. We assume that is not a legitimate argumentative tactic. Such a move is tantamount to the following line of thought: "I argue that all humans are mortal." I then meet an immortal human. Instead of saying, "I cannot categorize all humans as mortal," I now say, "Some mortal things live forever." It is, admittedly, common for philosophers to define technical terms as they see fit, but doing so runs the risk of failed communication and muddied waters. However, as it concerns the mechanistic vs. dynamical explanations debate, we ought to be clear about what commitments each explanatory framework makes and, especially, pay attention to the features that make differences in their being different. Using differential equations, as mentioned above, is not one of those commitments. Understanding a phenomenon as component or interaction dominant is. Such commitments are not readily encompassed by the other framework, which is why they are different approaches in the first place (for more detailed discussion of this issue, we recommend Issad & Malaterre, 2015).

5. Explanatory Pluralism

In the preceding sections, we presented bird flocking as a case in the life sciences that is justifiably given both a mechanistic and dynamical explanation for various features at the same biobehavioral scale. The mechanistic strategy treats the flock as a collection of individual units. Bird orientation and scale-free coordination are explained via the maximum entropy model, which regards individual birds as following simple rules similar to individual magnets. The

dynamical strategy treats the flock as a single complex system that emerges from the interaction of individual units. Bird velocity and scale-free coordination are explained via the superdiffusion model, which regards the flock as a single mass where individual birds are moved by and move the system via a diffusive process. Each explanation aims at the same general question: How does the behavior of bird *X* navigating amongst its nearest neighbors, Y_1-Y_7, result in scale-free correlations? However, each strategy provides a different kind of explanation for different features of the same phenomenon: bird location and bird velocity. All of the explanations (i.e., models) occur at the same scale of investigation, namely, the biobehavioral level at which murmurations occur. Is there a single explanatory strategy that will account for all aspects of this single scale? Specifically, is there justifiable reason to attempt to provide a mechanist account of velocity or a dynamical account of location? We do not believe so. Though there is overlap in some of the explained behavior (i.e., scale-free coordination), there are essential features of the phenomenon that are excluded by the explanations of each explanatory strategy. Consequently, the features of the bird flock at the biobehavioral scale are not all appropriately conceptualized as mechanisms (e.g., component dominant) or dynamical systems (e.g., interaction dominant). This is because the flock both has mechanisms and is a dynamical system at the same scale of investigation.

It is reasonable to see hints of the predicament of underdetermination in science as an underlying issue (Stanford, 2009). Specifically, one could claim there is not yet enough evidence to arbitrate the issue. Perhaps a mechanist can say, “My strategy explains bird orientation, it will eventually explain bird location too!” Perhaps a dynamicist can say, “My strategy explains bird location, it will eventually explain bird orientation too!” Nonetheless, underdetermination is not an issue here, nor are issues concerning empirically equivalent theories (van Fraassen, 1980).

When placed within different investigative frameworks, bird flocking can be conceptualized in different ways. For example, if the bird flock is a component-dominant system, then all of its features are additively and linearly related. On the other hand, if the bird flock is an interaction-dominant system, then all of its features are nonlinearly related. The challenge with applying one set of theoretical commitments (e.g., component or interaction dominance) to this case is that there is empirical evidence for both being applicable to different features. It seems that there is not empirical equivalence among mechanistic and dynamical strategies because each strategy is applied to different features, namely, orientation and velocity. If certain theoretical commitments are accurate, namely, if certain features of the flock are properly characterized as component dominant and others as interaction dominant, then it would be unproductive to attempt to fit the square peg of component-dominant phenomena into the round hole of dynamical explanations or the round peg of interaction-dominant phenomena into the square hole of mechanistic explanations.

With that said, in light of the possibility of giving two equally viable explanations of different aspects of the same phenomenon, we believe that starting investigations from positions other than pluralism can result in the unjustifiable application of theoretical commitments. Starting from a commitment to pluralism allows one to utilize various explanatory tools without the limitations that come with stringent adherence to single strategies. A lesson to take from a commitment to pluralism is that the study of a single phenomenon may simultaneously require multiple kinds of explanatory frameworks. This is not because the data is underdetermined or there is empirical equivalency. This is because the data from a single phenomenon are the result of very different kinds of causes, namely, causes that in one instance are best treated mechanistically and in another best treated dynamically. Insisting on just one style of explanation

will leave us in the position of being able to explain bird orientation or bird velocity, but not both.

Let us revisit the argument presented in the first section. We have shown that (P1) mechanistic explanations appropriately account for some natural phenomena, here, bird orientation, which is a phenomenon not readily reducible to another explanatory framework (P2), such as a dynamical one. We have shown that (P3) dynamical explanations appropriately account for some natural phenomena, here, bird velocity, which is a phenomenon not readily reducible to another explanatory framework (P4), such as a mechanistic one. Starling murmurations are a natural phenomenon that exhibit various features amenable to different kinds of explanatory strategies (P5): mechanistic approach for bird orientation and dynamical approach for bird velocity. Due to key commitments of each (P6), mechanistic strategies (e.g., component dominance) do not reduce to dynamical approaches, and dynamical strategies (e.g., interaction dominance) do not reduce to mechanistic approaches. Thus (C1), starling murmurations require multiple explanatory strategies to explain various features at the same biobehavioral scale of investigation. Moreover (C2), starling murmurations require both mechanistic (i.e., orientation) and dynamical (i.e., velocity) explanatory strategies to be more fully understood.

6. Conclusion

We view explanatory pluralism as a virtue. Starting from a position of pluralism is a virtue not only in scientific inquiry but other forms of inquiry as well. It is likely that some see explanatory pluralism as a bad position to subscribe to. Examples include those who adhere to the mechanism-only or dynamical-only explanatory framework points of view, as well as those who think that what makes dynamical explanations interesting can readily be subsumed by

mechanistic approaches. Others likely not to be satisfied with explanatory pluralism include those who want necessary and sufficient conditions for such concepts as “science,” “cause,” and “explanation.” However, those who are interested in the practice of science will see that there is no matter of fact as to which kind of explanation holds the position of primacy over all others (cf. Feyerabend, 1975/2010). Furthermore, those interested in the practice of science will also see that there is no adherence to a single theoretical commitment, come what may (cf. Quine, 1951). An honest investigator, be she a biologist, philosopher, or physicist, will accept the primacy of phenomena over commitment to ideology. Moreover, pluralism is not just the beginning, but also sometimes the end. That is to say, that there are different kinds of explanations of the same system; or, as we show here, different kinds of explanations—with some opposing claims; e.g., component vs. interaction dominance—of the different but closely related aspects of the same system. This is not necessarily a case of underdetermination, or a failure to find the right mechanistic or dynamical explanation. This can be the end state. In this case, the orientations of individual birds in the flock are mechanistically explained, while their velocity is dynamically explained. There is no reason to think that starling murmurations are unique in this respect.

References

Bechtel, W. (2008). *Mental mechanisms: Philosophical perspectives on cognitive neuroscience*. New York, NY: Routledge.

Bechtel, W., & Abrahamsen, A. (2005). Explanation: A mechanist alternative. *Studies in History and Philosophy of Biological and Biomedical Sciences*, *36*, 421-441.

Bechtel, W., & Abrahamsen, A. (2006). In search of mitochondrial mechanisms: Interfield excursions between cell biology and biochemistry. *Journal of the History of Biology*, *40*, 1-33.

Bechtel, W., & Abrahamsen, A. (2010). Dynamic mechanistic explanation: Computational modeling of circadian rhythms as an exemplar for cognitive science. *Studies in History and Philosophy of Science*, *41*, 321-333.

Bechtel, W., & Abrahamsen, A. (2011). Complex biological mechanisms: Cyclic, oscillatory, and autonomous. In C. Hooker (Ed.), *Handbook of the philosophy of science. Volume 10: Philosophy of complex systems* (pp. 257-285). Oxford Waltham: North Holland.

Bechtel, W., & Abrahamsen, A. A. (2013). Thinking dynamically about biological mechanisms: Networks of coupled oscillators. *Foundations of Science*, *18*, 707-723.

Bechtel, W., & Richardson, R. C. (1993/2010). *Discovering complexity: Decomposition and localization as strategies in scientific research, second edition*. Cambridge, MA: MIT Press.

Beer, R. D. (2000). Dynamical approaches to cognitive science. *Trends in Cognitive Sciences*, *4*, 91-98.

ben-Avraham, D., & Havlin, S. (2004). *Diffusion and reactions in fractals and disordered systems*. Cambridge, MA: Cambridge University Press.

Bialek, W., Cavagna, A., Giardina, I., Mora, T., Silvestri, E., Viale, M., & Walczak, A. M. (2012). Statistical mechanics for natural flocks of birds. *Proceedings of the National Academy of Sciences*, *109*, 4786-4791.

Brown, C. (2007). *Differential equations: A modeling approach*. Los Angeles, CA: SAGE Publications.

Carello, C. & Moreno, M. A. (2005). Why nonlinear methods? In M. A. Riley & G. C. Van Orden (Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences* (pp. 1-25). United States: National Science Foundation.

Cavagna, A., Cimarelli, A., Giardina, I., Parisi, G., Santagati, R., Stefanini, F., & Viale, M. (2010). Scale-free correlations in Starling flocks. *Proceedings of the National Academy of Sciences*, *107*, 11865-11870.

Cavagna, A., Queiros, S. M. D., Giardina, I., Stefanini, F., & Viale, M. (2013a). Diffusion of individual birds in starling flocks. *Proceedings of the Royal Society B*, *280*: 20122484. doi: 10.1098/rspb.2012.2484

Cavagna, A., Giardina, I., & Ginelli, F. (2013b). Boundary information inflow enhances correlation in flocking. *Physical Review Letters*, *110*, 168107. doi:10.1103/PhysRevLett.110.168107

Chemero, A. (2009). *Radical embodied cognitive science*. Cambridge, MA: MIT Press.

Chemero, A., & Silberstein, M. (2008). After the philosophy of mind: Replacing scholasticism with science. *Philosophy of Science*, *75*, 1-27.

Chialvo, D. R. (2018). Life at the edge: Complexity and criticality in biological function. *Acta Physica Polonica B*, *49*(12), 1955-1979.

Craver, C. F. (2005). Beyond reduction: Mechanisms, multifield integration and the unity of

neuroscience. *Studies in History and Philosophy of Biological and Biomedical Sciences*, *36*, 373-395.

Craver, C. F. (2006). When mechanistic models explain. *Synthese*, *153*, 355-376.

Craver, C. F. (2007). *Explaining the brain.* Oxford: Oxford University Press.

Craver, C. F., & Alexandrova, A. (2008). No revolution necessary: Neural mechanisms for economics. *Economics and Philosophy*, 24, 381-406.

Craver, C. F., & Bechtel, W. (2007). Top-down causation without top-down causes. *Biology and Philosophy*, *22*, 547-563.

Craver, C. F., & Darden, L. (2005). Introduction. *Studies in History and Philosophy of Biological and Biomedical Sciences*, *36*, 233-244.

Craver, C. F., & Darden, L. (2013). *In search of mechanisms: Discoveries across the life sciences*. Chicago, IL: University of Chicago Press.

Dale, R. (2008). The possibility of a pluralist cognitive science. *Journal of Experimental and Theoretical Artificial Intelligence*, *20*, 155-179.

Dale, R., Dietrich, E., & Chemero, A. (2009). Explanatory pluralism in cognitive science. *Cognitive Science*, *33*, 739-742.

Darden, L., & Craver, C. (2002). Strategies in the interfield discovery of the mechanism of protein synthesis. *Studies in History and Philosophy of Biological and Biomedical Sciences*, *33*, 1-28.

Eliasmith, C., & Anderson, C. H. (2003). *Neural engineering: Computation, representation, and dynamics in neurobiological systems*. Cambridge, MA: MIT Press.

Favela, L. H. (2020a). Dynamical systems theory in cognitive science and neuroscience. *Philosophy Compass*, *15*(8), e12695, 1-16. doi:10.1111/phc3.12695

Favela, L. H. (2020b). The dynamical renaissance in neuroscience. *Synthese*. doi:10.1007/s11229-020-02874-y

Favela, L. H., & Martin, J. (2017). "Cognition" and dynamical cognitive science. *Minds and Machines*, *27*, 331-355. doi:10.1007/s11023-016-9411-4

Feyerabend, P. (1975/2010). *Against method, fourth edition*. New York, NY: Verso.

Glennan, S. (2005). Modeling mechanisms. *Studies in History and Philosophy of Science Part C: Studies in History and Philosophy of Biological and Biomedical Sciences*, *36*(2), 443-464.

Glennan, S., & Illari, P. (Eds.). (2018). *The Routledge handbook of mechanisms and mechanical philosophy*. New York, NY: Routledge.

Godfrey-Smith, P. (2010). Causal pluralism. In H. Beebee, C. Hitchcock, & P. Menzies (Eds.), *The Oxford handbook of causation* (pp. 326-337). Oxford: Oxford University Press.

Harnad, S. (1993). Grounding symbols in the analog world with neural nets. *Think*, *2*(1), 12-78.

Holden, J. G., Van Orden, G. C., & Turvey, M. T. (2009). Dispersion of response times reveals cognitive dynamics. *Psychological Review*, *116*, 318-342.

Ivancevic, V. G., & Ivancevic, T. T. (2007). *Computational mind: A complex dynamics perspective*. New York, NY: Springer.

Izhikevich, E. M. (2007). *Dynamical systems in neuroscience: The geometry of excitability and bursting*. Cambridge, MA: MIT Press.

Izhikevich, E. M. (2010). Hybrid spiking models. *Philosophical Transactions of the Royal Society A*, *368*, 5061-5070.

Issad, T., & Malaterre, C. (2015) Are dynamic mechanistic explanations still mechanistic? In P.-A. Braillard & C. Malaterre (Eds.), *Explanation in biology: An enquiry into the diversity*

of explanatory patterns in the life sciences (pp. 265-292). Dordrecht: Springer.

Kaplan, D. M. (2018). Mechanisms and dynamical systems. In S. Glennan & P. Illari (Eds.), *The Routledge handbook of mechanisms and mechanical philosophy* (pp. 267-280). New York, NY: Routledge.

Kaplan, D. M., & Bechtel, W. (2011). Dynamical models: An alternative or complement to mechanistic explanations? *Topics in Cognitive Science*, *3*, 438-444.

Kaplan, D. M., & Craver, C. F. (2011). The explanatory force of dynamical and mathematical models in neuroscience: A mechanistic perspective. *Philosophy of Science*, *78*, 601-627.

Kattas, G. D., Xu, X. - K., & Small, M. (2012). Dynamical modeling of collective behavior from pigeon flight data: Flock cohesion and dispersion. *PLoS Computational Biology*, *8*(3): e1002449, 1-15. doi:10.1371/journal.pcbi.1002449

Kelso, J. A. S. (1997). *Dynamic patterns: The self-organization of brain and behavior*. Cambridge, MA: MIT Press.

Kuhlmann, M., & Glennan, S. (2014). On the relation between quantum mechanical and neo-mechanistic ontologies and explanatory strategies. *European Journal for Philosophy of Science*, *4*, 337-359.

Lamb, M., & Chemero, A. (2018). Interacting in the open: Where dynamical systems become embodied and embedded. In A. Newen, L. de Bruin, & S. Gallagher (Eds.), *The Oxford handbook of 4E cognition* (pp. 147-162). New York, NY: Oxford University Press.

Levy, A., & Bechtel, W. (2013). Abstraction and the organization of mechanisms. *Philosophy of Science*, *80*, 241-261.

Li, C., Zhao, Z., & Chen, YQ. (2011) Numerical approximation of nonlinear fractional differential equations with subdiffusion and superdiffusion. *Computers and Mathematics*

with Applications, *62*, 855-875.

Love, A. C. (2012). Hierarchy, causation and explanation: Ubiquity, locality and pluralism. *Interface Focus*, *2*, 115-125.

Machamer, P., Darden, L., & Craver, C. F. (2000). Thinking about mechanisms. *Philosophy of Science*, *67*, 1-25.

Mitchell, S. D. (2002). Integrative pluralism. *Biology and Philosophy*, *17*, 55-70.

Newman, J. (2008). *Physics of the life sciences*. London: Springer.

Piccinini, G., & Craver, C. (2011). Integrating psychology and neuroscience: Functional analyses as mechanism sketches. *Synthese*, *183*, 283-311.

Povich, M., & Craver, C. F. (2018). Mechanistic levels, reduction, and emergence. In S. Glennan & P. Illari (Eds.), *The Routledge handbook of mechanisms and mechanical philosophy* (pp. 185-197). New York, NY: Routledge.

Procaccini, A., Orlandi, A., Cavagna, A., Giardina, I., Zoratto, F., Santucci, D., Chiarotti, F., Hemelrijk, C. K., Alleva, E., Parisi, G., & Carere, C. 2011. Propagating waves in Starling, *Sturnus Vulgaris*, flocks under predation. *Animal Behaviour*, *82*, 759-765.

Pylyshyn, Z. W. (1984). *Computation and cognition: Toward a foundation for cognitive science*. Cambridge, MA: MIT Press.

Quine, W. V. (1951). Two dogmas of empiricism. *The Philosophical Review*, *60*, 20-43.

Reiss, J. (2007). Do we need mechanisms in social science? *Philosophy of the Social Sciences*, *37*, 163-184.

Richardson, M. J., & Chemero, A. (2014). Complex dynamical systems and embodiment. In L. Shapiro (Ed.), *The Routledge handbook of embodied cognition* (pp. 39-50). New York, NY: Routledge.

Riley, M. A., & Holden, J. G. (2012). Dynamics of cognition. *WIREs Cognitive Science*, *3*, 593-606.

Ross, L. N. (2015). Dynamical models and explanation in neuroscience. *Philosophy of Science*, *82*, 32-54.

Sandeman, K., Hopwood, C., Brook, D., & Sallows, L. (2008). Ferromagnetic materials. *DoITPoMS*. Department of Materials Science and Metallurgy, University of Cambridge. Retrieved January 16, 2013, from www.doitpoms.ac.uk/tlplib/ferromagnetic/index.php

Silberstein, M. (2021). Constraints on localization and decomposition as explanatory strategies in the biological sciences 2.0. In F. Calzavarini & M. Viola (Eds.), *Neural mechanisms: New challenges in the philosophy of neuroscience* (pp. 363-393). Cham, Switzerland: Springer.

Silberstein, M., & Chemero, A. (2013). Constraints on localization and decomposition as explanatory strategies in the biological sciences. *Philosophy of Science*, *80*, 958-970.

Stanford, K. (2009). Underdetermination of scientific theory. In E. N. Zalta (Ed.), *The Stanford encyclopedia of philosophy*. Retrieved January 16, 2013, from http://plato.stanford.edu/archives/win2009/entries/scientific-underdetermination/

Stepp, N., Chemero, A., & Turvey, M. T. (2011). Philosophy for the rest of cognitive science. *Topics in Cognitive Science*, *3*, 425-437.

Sterelny, K. (1996). Explanatory pluralism in evolutionary biology. *Biology and Philosophy*, *11*, 193-214.

Sternberg, S. (1969). The discovery of processing stages: Extensions of Donders' method. *Acta Psychologica*, *30*, 276-315.

Sternberg, S. (2011). Modular processes in mind and brain. *Cognitive Neuropsychology*, *28*, 156-

208.

Strogatz, S. H. (2018). *Nonlinear dynamics and chaos: With applications to physics, biology, chemistry, and engineering* (2nd Edition). New York, NY: CRC Press.

Suppes, P. (1978). The plurality of science. In P. Asquith, & I. Hacking (Eds.), *PSA: Proceedings of the biennial meeting of the Philosophy of Science Association, Volume Two: Symposia and invited papers* (pp. 3-16). East Lansing, MI: Philosophy of Science Association.

van Fraassen, B. C. (1980). *The scientific image*. New York, NY: Oxford University Press.

van Gelder, T. (1998). The dynamical hypothesis in cognitive science. *Behavioral and Brain Sciences*, *21*, 615-665.

Wright, C. D., & Bechtel, W. (2006). Mechanisms and psychological explanation. In D. M. Gabbay, P. Thagard, & J. Woods (Eds.), *Handbook of the philosophy of science. Volume 12: Philosophy and psychology* (pp. 31-79). Elsevier.

Yoshimi, J. (2012). Supervenience, dynamical systems theory, and non-reductive physicalism. *British Journal for the Philosophy of Science*, *63*, 373-398.